Liver Lesions Classification System using CNN with Improved Accuracy

Swapnil V.Vanmore[1], Sangeeta R.Chougule[2]
[1]*Electronics Engineering, Department of Technology, Shivaji University,Kolhapur,Maharashtra,India*
[2]*Electronics & Telecommunication Department, KITS college of Engineering, Kolhapur, Maharashtra, India*

Abstract

In this paper, the liver lesions classification system for CT images use deep learning (CNN)model with improved accuracy has proposed. The sequential model of CNN architecture with I/P convolution layer, Hidden convolution layer, and O/P convolution layer for CT images have been used to classify liver lesions. TensorFlow-2.0 is used to make an image with varying image qualities.The proposed network is used for CT images with an image size of 65×65, 60×60, 50×50 for which liver lesions classification accuracy of 99%,97%,95% respectively are achieved. The regularization technique used in proposed N/W has helped to improve the accuracy and minimization over fitting problem. The classification accuracy improvement has justified by comparing the proposed research work with other researcher's work.

Keywords: Computer-Aided-Diagnosis(CAD); Relu (Rectified linear unit); Digital Imaging and Communication in Medicine(DICOM);Computed Tomography(CT);Convolution Neural Network(CNN).

*Corresponding author Email: swapnil.v96@gmail.com

1. Introduction

In the human body there are several types of cancer. Among them, liver lesions are a form of cancer that causes 7,45,000 deaths worldwide every year. The liver one of its most prevalent organs used to grow metastases inside the body. [1]. Liver lesions are groups of abnormal cells present on itself or spread from the liver to the other part of the body. Liver lesions have different size, shape, location of different patients. Level of liver lesions shown in Fig. 1 a) Low (Primary) Level lesions, b) Medium Level lesions and c) High level lesions. The low-level liver lesions are categorized in various types viz Cyst and Hepatocellular Carcinoma (HCC), however high-level liver lesions is Metastases. Fig. 2 shows normal state liver CT images, and liver lesions Computed tomography images of type Cyst, HCC and Metastases. The Lesions do not shown to be easily prepared by human eyes or manually. Lesions do not have clear boundaries. The automatic segmentation techniques can be used for detection of Lesions boundary [2]. It is important to know the early diagnosis of liver disorders for successful cancer treatment Although diagnostic imaging is used to detect cancer, it is also utilised to treat it. It is the most useful method. In particular, there have been recent developed advances in the medical imaging system,accessionof high quality resolution CT or MRI data sets is enabled, making it possible to detect small Lesions (early stage) through the use of high-resolution CT images. CT Imaging method is one of the most common methods for detecting, diagnosing and delineation of liver lesions. Doctor's experience is very important in image quality based diagnostic, they decide the existence or absent of a lesions fragment through slices based on their medical definition, which is a more time-require and labour intensive task [3]. Therefore, in recenttechnologiesautomated Tumor detection has become an important research topic in CT images. In recent years researcher has done the work on extraction of the enhanced pattern by using Grouped Convolution Long Short Term Memory (GCLSTM) for getting the information of average precision for detection of liver lesions [4-5].

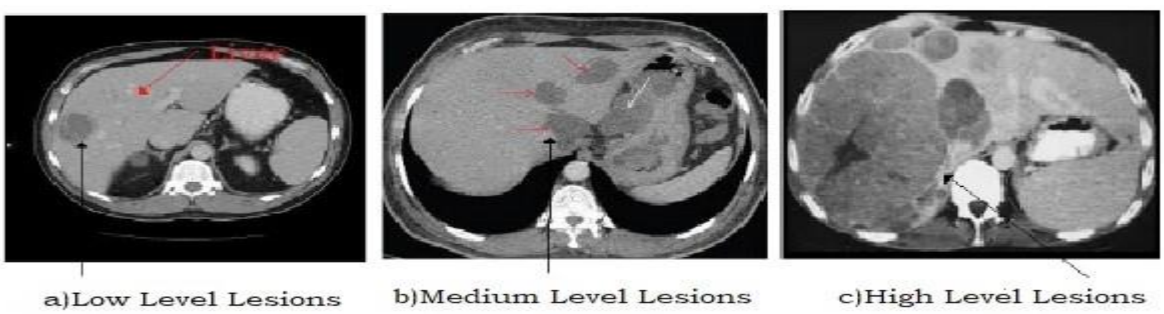


Figure 1: Liver CT Images Lesions Levels

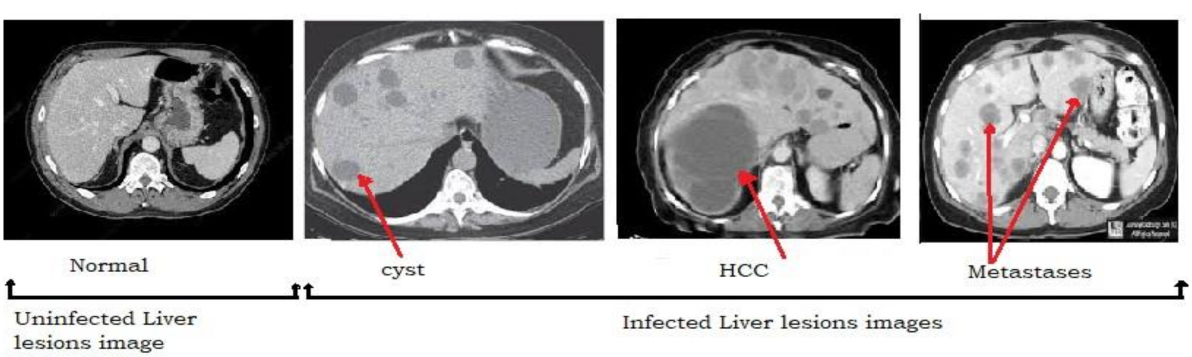


Figure 2: Normal (Uninfected) and Liver Lesions (Infected) CT images

The Computer Aided Diagnosis (CAD) for liver lesions classification using the deep learning method has implemented for the improvement of the classification accuracy up to 91.21% [6-7]. The rate of true positives and false positives is computed. using Fully Convolution Network (FCN) of liver metastases detection in CT examination[1]. The ground truth, the center of mass and mass lesions classification done by using Euclidian distance method for calculation of accuracy, precision, recall, parameters[7]. The End to End Discriminating deep network for classification different lesions types has implemented with classification an accuracy of 96% in [8]. The regularization method and dropout techniques have adopted in the neural network on supervised learning tasks for reduction of the over fitting problem and enhancement of the the network performance [9]. BovW (Bag of visual words) method has used for the automated diagnosis of Cyst, and Metastases types of liver lesions with an accuracy of 93% for combined data set [10]. The Tensor based sparse representation for classification of Hemangioma (HEM) and cyst liver lesions with a classification accuracy of 89.29% have obtained [11].

2. Convolution Neural Network (CNN) Architecture

The generalized CNN architecture consists main three layers are input convolution Layer, hidden convolution layer, output convolution layer as shown in Fig. 3. Liver images are applied to the input layer as set of data .the output features are taken from the output layer, A hidden layer is the layer that located between both the input and output layers.

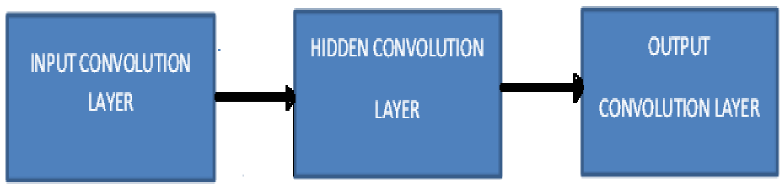


Figure 3: Generalized block diagram of the CNN

In convolution layer, neuron is the main important element. This network consists of neurons that have diverse learning weights and biases. The number of inputs obtained by each neuron is equal to the number of inputs received from every neuron, takes a weighted sum over them. It responses with outcome after going via aRelu activation function. Convolution layers systematically applying filters to input images for creating feature maps. A convolution layer put together in the deep models allows lower level features (e.g. lines) to be learned by layers adjacent to the input. Layers deeper in the model from that learns higher-level features like specific objects or shapes. The layers will get more information as they combine to generate a more complex pattern.This architecture allows it to focus first on the lower level feature of the hidden layer in the N/W, then These larger upper-level features of a subsequent hidden layer are integrated.This is the one of the reason for selecting of the CNN method for Image Recognition and classification. This neuron's output is written into the convolution layer. is given by equation 1.

$$z_{i,j,k} = b_k + \sum_{u=0}^{f_h-1} \sum_{v=o}^{f_w-1} \sum_{k'}^{f_{n'}-1} x_{i',j',k'} \cdot w_{u,v.k',k}$$
$$with \begin{cases} i' = i \times s_h + u \\ j' = j \times S_w + v \end{cases} \qquad (1)$$

where $z_{i,j,k}$is the output of neuron at i^{th}row,j^{th} column in k^{th}feature map of the convolution layer(l). $s_h$and s_w are the vertical strides and horizontal strides, f_h and f_w are the relevant field's height and widths, as well as $f_{n'}$is the number of features inside the layer before this one (l– 1).$x_{i',j',k'}$is the output of neuron ati^{th}row,j^{th} column in k^{th}feature map of the previous convolution layer(l-1). $w_{u,v.k',k}$ is the connection weight between any neuron in feature map k of the layer l and its input located ate row u, column v and feature map,k′b_k bias term for feature map k.

The CNN's activation function is highly essential. It applies before the pooling layer. The Relu (Rectified linear unit) activation function written in Eq. 2 is used to activate the nodes of a hidden layer [12], whereas sigmoid activation function of Eq. 3 is used at the output layer for binary classification

$$F(x) = \begin{cases} 0 & x < 0 \\ x & x >= 0 \end{cases} \qquad (2)$$

$$F(x)=\frac{1}{1-e^{-x}} \qquad (3)$$

The cross-entropy loss function as given in Eq. 4 is used for binary classification in the CNN.

$$S = -\sum_x p(x)p(x) \qquad (4)$$

where S is the cross-entropy loss for discrete random variable x with probability distribution function p(x). The bigger the entropy loss, will more uncertain the distributions, and the lesser the amount, more the definite the distribution of variables.

3. Design and Implementation of the Proposed CNN System

For classification (i.e. diagnosis) of liver lesions, the convolution neural network (CNN) has developed and implemented. CT scan images required for this proposed neural network have collected from Kolhapur cancer hospital center, Kolhapur, Maharashtra, India. Total 450 images of 50 patients have collected, these images are of 30 to 60 year Age group patients from which 70% male and 30% female. The collected images are in DICOM format (Digital Imaging and Communication in Medicine).

a)Normal (Uninfected CT scan images)

b)Abnormal(Infected (Metastases)CT scan Images)

Figure 4: Normal and Abnormal (Uninfected and Infected (Metastases)) CT Images, Courtesy: Kolhapur Cancer Hospital Center, Kolhapur, Maharashtra, India

The memory size of each DICOM images is generally 50 Kb to 172 Kb. To minimize the data's amount of memory, the lossy compression technique has used in which Huffman coding method and sequential coding technique have been used. The compressed image is of JPEG format, 8 bit length, gray scale, and up to 70 Kb memory Size. Liver lesions images (Infected images) and normal liver images (uninfected Images) are divided into two separate groups of The proposed network will be trained and validated using 200 images each.This set of data is split in training data & validation data, 80% of the data set is used for training the CNN network and 20% of the set of a data is used to validate CNN network. The remaining 50 images (infected and uninfected) have been taken to test the proposed network system. Some of different images from the set of data are shown in Fig. 4. The figure shows a) normal (uninfected) and b) liver lesions (Infected) images type of Metastases.

Liver data set are resized to 65×65 pixels prior being sent to the CNN network, without it being zero-padded and adjusted. The proposed sequential model of CNN architecture shown in Fig 5. It is made up of three layers: an I/P layer, a hidden layer, and an O/P layer. The I/P layer uses 3×3 kernel size with stride 1, it is a attended layer with shape 65×65, which means that images are 65×65 pixels with the only one color channel (gray scale).

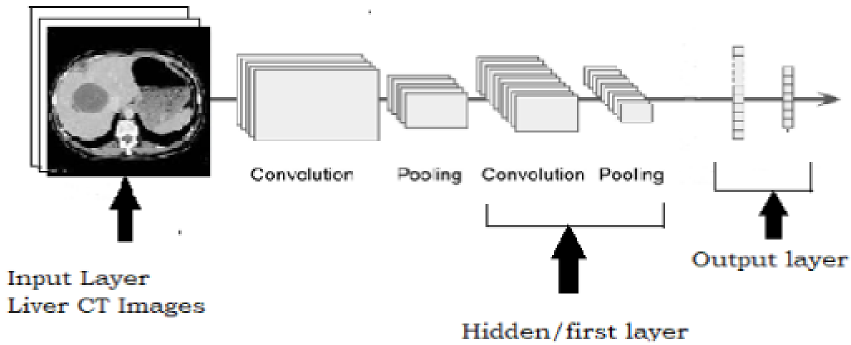


Figure 5: Proposed CNN Architecture

Table 1: Proposed CNN structure.

Layer (type)	Output Shape	Parameter
conv2d (Conv2D)	(None, 62, 62, 16)	448
max _pooling2d	(None, 31, 31, 16)	0
(maxPooling2D) droput	(None, 31, 31, 16)	0
conv2d_1 (Conv2D)	(None, 29, 29, 32)	4640
maxpooling2d_1(max pooling2d_1)	(None, 14, 14, 32)	0
dropout_1(Dropout)	(None, 14, 14, 32)	0
fatten (Flatten)	(None,6272)	0
dense(Dense)	(None,64)	401472
dropout_2 (Dropout)	(None,64)	0
dense_1(Dense)	(None,1)	65
Total params: 406,625		
Trainable params: 406,625		
Non-trainable params: 0		

For reducing computation time small size images have preferred, so images are resized to 65×65. Next to the input layer is the two-dimensional convolution network, it is developed using 16 number of filters with size 3×3. Just atI/P layer, the Relu activation function has been used.To reduce the computation loads, I/P images are sub- sampled (i.e. shrink) by using 2D max-pooling of 2×2 kernel size with stride 1 and no padding. The hidden layer is implemented with 32 number of 2D convolution filter of kernel size 3×3. The activation function used in the hidden layer is the Relu function, for dimension reduction the 2D max-pool of kernel size 2×2 has been used. Next is a fully connected network composed of one hidden dense layer and one dense output layer. The hidden dense layer is 1D layer which consists of 64 number of units with Relu activation function however the o/p layer consists of one unit with a sigmoid activation function. The CNN architecture is trained with the help of training data with the batch size is 16. The proposed CNN model is compiled by selecting Adam optimizer, and the binary cross-entropy loss function. The number of epoch selected for compilation is 5 where 320 steps per epoch based on the number of training images have been selected for training. The over Fitting is reduced by using regularization technique. For this technique neurons of each layer are dropped by 20%, 30% and 50% dropout rate appliedat I/P layer & hidden Layer and O/P layer respectively.The proposed CNN has designed and implemented using Tensor Flow 2.0 module on Python 3.7, and executed on TensorFlow Processing Unit(TPU) provided Google Colab. The summary of the proposed CNN structure is given in Table 1.

4. Results and Discussion:

For each epoch, the model was trained for 5 iterations with 16 small batch size.It has been observed that the accuracy of the classification is increasing after each epoch, however, loss decreases. The trained model is validated using validation data. Three different image size 65×65, 60×60, 50×50 has taken for the analysis. Train accuracy, validation data accuracy, training data loss, and validation loss data were collected and are given in Table 2 and Table 3.

Table 2: Training accuracy and loss for different image sizes

Image size	Epoch	Training	
		Accuracy	Loss
65*65	1st Epoch	0.7065	0.5578
	2nd Epoch	0.9341	0.2572
	3rd Epoch	0.9529	0.1578
	4th Epoch	0.9341	0.123
	5th Epoch	0.994	0.7162
60*60	1st Epoch	0.6287	0.6257
	2nd Epoch	0.8323	0.424
	3rd Epoch	0.9341	0.2683
	4th Epoch	0.964	0.1443
	5th Epoch	0.97	0.1021
50*50	1st Epoch	0.6047	0.6512
	2nd Epoch	0.794	0.4229
	3rd Epoch	0.8862	0.2601
	4th Epoch	0.9281	0.1764
	5th Epoch	0.952	0.118

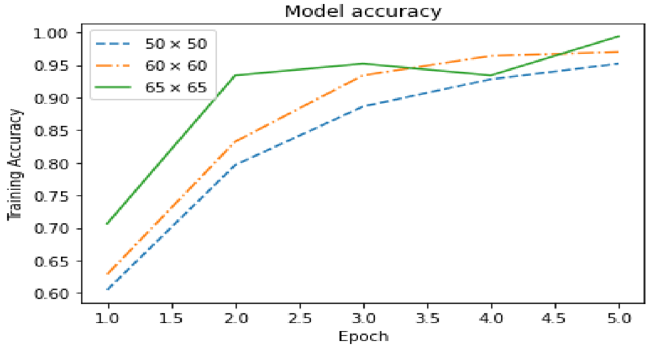
Table 3: Validation accuracy and loss for different image sizes

Image size	Epoch	Training	
		Accuracy	Loss
65*65	1st Epoch	0.6585	0.5426
	2nd Epoch	0.8536	0.3405
	3rd Epoch	0.9024	0.2197
	4th Epoch	0.9268	0.2319
	5th Epoch	0.9024	0.213
60*60	1st Epoch	0.5609	0.6214
	2nd Epoch	0.8556	0.4336
	3rd Epoch	0.9024	0.304
	4th Epoch	0.8292	0.2858
	5th Epoch	0.9024	0.2858
50*50	1st Epoch	0.6097	0.6195
	2nd Epoch	0.6585	0.602
	3rd Epoch	0.878	0.3717
	4th Epoch	0.9024	0.251
	5th Epoch	0.9024	0.2271

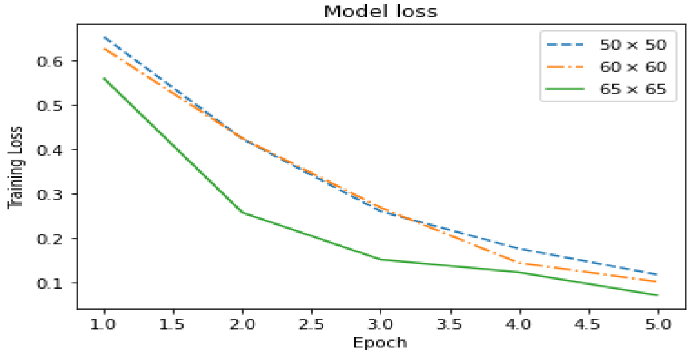
For the training and validation data sets, the accuracy versus epochs and loss versus epochs are plotted and are shown in Fig. 6 and Fig. 7. From the graphs of Fig. 6a and Fig. 7a, it has been noticed that the maximum training accuracy is 99 % at 5th epoch, whereas the maximum validation accuracy of 92.68 % is obtained at 4th epoch. Fig. 6b and Fig. 7b shows Loss versus Epoch for Training and Validation data. It has been noticed from graphs that training and validation loss decreases after each epoch so the model is not over Fitted. Over Fitting problem arises in a small data base but in the proposed system the regularization technique has been adopted to minimize the over Fitting.

For a performance measure of the proposed CNN, 50 testing CT images of size 65×65 have been used. These testing images are of two classes, 25 normal (Uninfected) CT images are of class 1 and 25 abnormal (infected (Metastases)) CT images are of class 0. These images have been applied to a trained CNN model to get the confusion matrix. The Scikit-image and Tensor Flow modules have been used in python to obtain a confusion matrix as shown in Fig. 8. Using this matrix performance parameters such as True Positive(TP)= 24, False

Positive(FP) = 1, False Negative(FN) = 2 and True Negative(TN) = 23 have been obtained. The performance metrics of the proposed CNN model are calculated as follows.

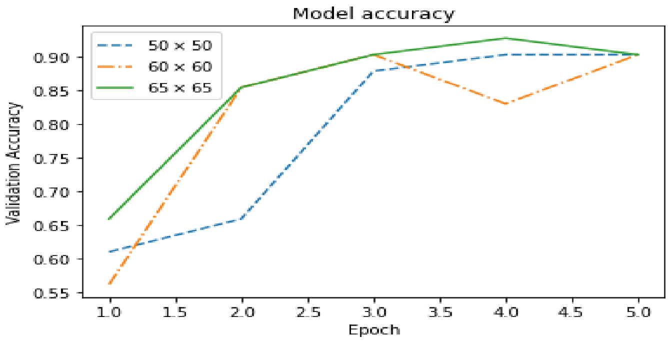


6. (a) Training accuracy versus epochs for different image sizes

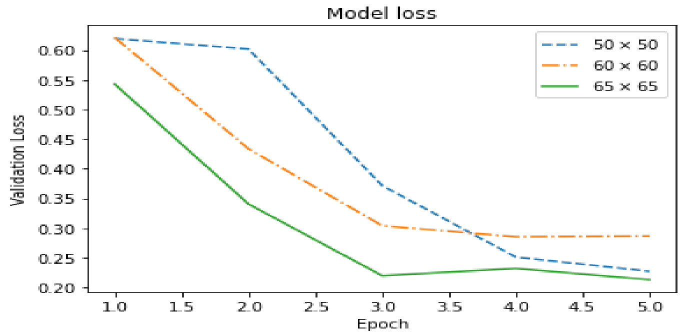


6. (b)Training loss versus epochs for different image sizes

Figure 6: Model accuracy and loss for training data



7.(a)Validation accuracy versus epochs for different image sizes



7. (b)Validation loss versus epochs for different image sizes

Figure 7: Model accuracy and loss for validation data

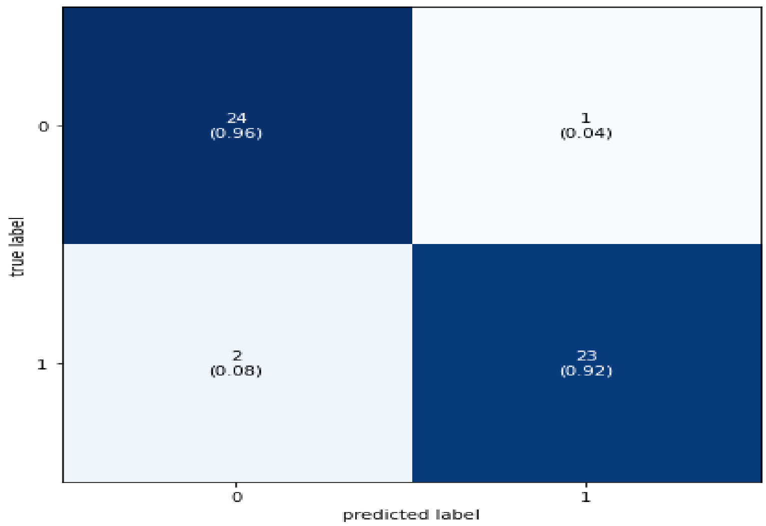


Figure 8: Confusion Metrics

$$\text{Precision}=\frac{TP}{TP+FP}=\frac{24}{24+1}=.96$$
$$\text{Recall}=\frac{TP}{TP+FN}=\frac{24}{24+2}=.92$$
$$\text{F1-Score}=\frac{2\times Recall\times Precision}{Recall+Precision}=0.93$$
$$\text{Specificity}=\frac{TN}{TN+FP}=\frac{23}{23+1}=0.95$$

Comparing the above parameters, it has been noticed that, Precision is greater than Recall and Specificity, whereas Specificity is greater than Recall. This indicates number of False Negative patients is higher than the number of False Positive patients. In the clinical point view number of the number of False Negative patients should be less than the number of False Positive patients. However, the F1-score is the best, indicates that there is still a good balance between Precision and Recall, indicates that the intended CNN performs well. The recommended system's prediction accuracy has been compared against state-of-the-art networks/methods developed by other researchers.It is given in the Table 4.

Table 4: Comparison of % classification accuracy with state- of-the-art networks/methods of other researchers

Author	**Network/ Method**	**Liver Lesions Types**	**%Classifications accuracy**
WeibinWANG et al 2018 [6]	(ResNet)Residual network	cyst	95.44
		HCC	91%
Francisco et al 2019[9]	End-to-End trainable deep network	Cyst	96%
IditDiamant et al 2015[7]	Bag-of- Visual-Words (BoVW) method	Cyst,HCC,Metastases	93%
Proposed network	**Sequential Model 2D CNN**	**Metastases**	**99%**

Table 5: Comparison of performance metrics of the proposed CNN model with state-of-the-art networks/methods of other researchers

Author	Network/ Method	Recall	specificity	Precision	F1-score
Francisco et al 2019[9]	End-to-End trainable deep network	0.94	0.85	1	0.92
IditDiamant et al 2015[7]	bag-of-visual-words (BoVW) method	0.96	0.9		
Proposed network	**Sequential Model 2D CNN**	**0.92**	**0.95**	**0.96**	**0.93**

In the observation, the proposed network's classification accuracy is higher than those of other researchers' work, it has been discovered.Performance metrics of the proposed network such as recall, precision, specificity and F1 score have been compared with networks proposed by other researchers as given in Table 5. The F1-score of the proposed network is approximately equal to one and matched with other researcher's network. Therefore, there is a balance between recall and precision, it represents the network's performance is better.

5. Conclusion

The proposed convolution neural network was designed and implemented. implemented for the classification of uninfected Liver images and metastases (infected) lesions images using Tensor Flow. For this network, the suggested network was trained and validated using CT scan images. The work was conducted on 65×65, 60×60, 55×55 image size. The maximum classification accuracy of 99%for image size 65×65 was obtained. However for 60×60 and 50×50 classification accuracy was 97%, 95% respectively. The proposed network was compared with previous works and was observed that the classification accuracy has been improved a lot. This accuracy was improved by adopting a regularization technique, for minimization of overfitting problem. In the observation, it has been noticed that F1 score is approximately equal to one, so it has maintained the balance between Recall and Precision. So it concluded that the proposed CNN model is the best for binary classification of infected and uninfected Liver CT images. Future scope of this work is to implement CNN for classification of the cyst, HCC, Metastases lesions type of the diseased liver with improved accuracy.

Conflict of interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1]. Ben-Cohen, I. Diamant, E. Klang, M. Amitai, and H. Greenspan, "Fully convolutional network for liver segmentation and lesions detection," in Deep learning and data labeling for medical applications, DLMIA 2016, Springer, 2016,pp. 77-85.(LNCS, volume 10008). https://doi.org/10.1007/978-3-319-46976-8_9

[2]. Wen Li "Automatic segmentation of liver tumor in ct images with deep convolutional neural networks," Journal of Computer and Communications, 3/11 (2015) 146. https://doi.org/10.4236/jcc.2015.311023

[3]. Y. Todoroki, X.-H.Han, Y. Iwamoto, L. Lin, H. Hu, and Y.-W. Chen, "Detection of liver tumor candidates from ctimages using deep convolutional neural networks," in International Conference on Innovation in Medicine and Healthcare. Springer, 2017, pp. 140-145. https://doi.org/10.1007/978-3-319-59397-5_15

[4]. Liang D, Lin L, Chen X, Hu H, Zhang Q, Chen Q, Iwamoto Y, Han X, Chen YW, Tong R, Wu J. "Multistream scale-insensitive convolutional and recurrent neural networks for liver tumor detection in dynamic ct images," in 2019 IEEE International Conference on Image Processing (ICIP). IEEE,Taipei, Taiwan 2019, pp. 794-798. https://doi.org/10.1109/ICIP.2019.8803730

[5]. D. Liang, L. Lin, H. Hu, Q. Zhang, Q. Chen, X. Han, Y.W. Chen "Combining convolutional and recurrent neural networks for classification of focal liver lesions multi-phase ct images," in International Conference on Medical Image Computing and Computer-Assisted Intervention. Springer, MICCAI 2018, pp. 666-675, (LNCS, volume 11071). https://doi.org/10.1007/978-3-030-00934-2_74

[6]. W. Wang, Y. Iwamoto, X. Han, Y.-W. Chen, Q. Chen, D. Liang, L. Lin, H. Hu, and Q. Zhang, "Classification of focal liver lesions using deep learning with Fine-tuning," in Proceedings of the 2018 International Conference on Digital Medicine and Image Processing, 2018, pp. 56-60.Okinawa Japan. https://doi.org/10.1145/3299852.3299860

[7]. I. Diamant, A. Hoogi, C. F. Beaulieu, M. Safdari, E. Klang, M. Amitai, H. Greenspan, and D. L. Rubin, "Improved patch-based automated liver lesion classification by separate analysis of the interior and boundary regions," IEEE journal of biomedical and health informatics, 20/6 (2015) 1585-1594. https://doi.org/10.1109/JBHI.2015.2478255

[8]. N. Shapira, J. Fokuhl, M. Schulthei_, S. Beck, F. K. Kopp, D. Pfei_er, J. Dangelmaier, G. Pahn, A. P. Sauter, B. Renger et al., "Liver lesion localisation and classification with convolutional neural networks: a comparison between conventional and spectral computed tomography," Biomedical Physics & Engineering Express, 6/1 (2020) 015038. https://doi.org/10.1088/2057-1976/ab6e18

[9]. F. Perdigon Romero, A. Diler, G. Bisson-Gregoire, S. Turcotte, R. Lapointe, F. Vandenbroucke-Menu, A. Tang, and S. Kadoury, "End-to-end discriminative deep network for liver lesion classification," arXiv preprint arXiv:1901.09483, 2019.

[10]. N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: a simple way to prevent neural networks from over fitting," The journal of machine learning research, 15/1 (2014) 1929-1958.

[11]. Wang, J. Li, X.-H. Han, L. Lin, H. Hu, Y. Xu, Q. Chen, Y. Iwamoto, and Y.-W. Chen, "Tensor-based sparse representations of multi-phase medical images for classification of focal liver lesions," Pattern Recognition Letters, 130 (2020) 207-215. https://doi.org/10.1016/j.patrec.2019.01.001

[12]. A. F. Agarap, 'Deep learning using rectified linear units (relu)," arXiv preprint arXiv:1803.08375, 2018.